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NORMALIZATION OF A REVERSE OSMOSIS DESALINATION PLANT

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ABSTRACT

Normalization is a very important procedure to be undertaken in any decision model so as to come up with comparable data which is not restricted by dimensions. Variations of several input parameters such as temperature, pressure feed TDS and membrane recovery ratio affect the standard operations of Reverse Osmosis (RO) plants which is why data normalization is required. It is necessary to normalize permeate flow rates in order to detect fouling caused by these varying operation conditions. This work seeks to standardize the operations of one of the major desalination plants in South Africa using Dupont powered FilmTec FTNorm reverse osmosis and a nanofiltration operating data normalization excel sheet.

KEYWORDS: Desalination, Reverse Osmosis & Normalization

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Original Article

1. INTRODUCTION

Researchers have been inspired to develop new strategies as a result of the necessity for a variety of decision-making procedures for dealing with various design difficulties; one of the strategies developed is normalization. Normalization can be defined as a transformation that uses a common scale to provide numerical and comparable input data. Following the collection of input data, some pre-processing is required to guarantee that the criteria are comparable, making the data suitable for decision modeling. The most important concern with normalizing techniques is how to choose the best one, that is, which one best represents the input/raw data. This is very important when we need to assure the aggregation/fusion of normalized criteria in multi-criteria decision models to derive scores for alternatives [1, 2]. According to Sankpal and Metre [3], normalization is a method for transforming data into a single standard canonical format by examining numerous parameters. RO membrane normalization for flux and salt passage data is of paramount importance for better RO plant design, performance efficiency calculations, and quality assurance of permeate water in accordance with World Health Organisation (WHO) and other standards [4]. Variation of several input parameters affect the standard operations of RO plants, hence data normalization is required.

2. NORMALIZATION OF THE PLANT

It is usual for reverse osmosis and nanofiltration system operating parameters to alter, causing the permeate flow and salt passage to shift. The observed permeate flow and salt passage must be standardized in order to discern between such typical events and performance variations owing to fouling or issues. Normalization is the process of comparing actual performance to a reference performance while accounting for the effects of operating conditions. The data is analyzed to see if the performance of the membrane system has altered over time. This is referred to as normalization [5].

There are several types of normalization techniques and these include, but are not limited to, those shown in Table 1.

Table 1: Selected Normalization Techniques

Normalization technique	Condition of use	Formulae	Reference
Linear (Max)	Benefit criteria	$n_{ij} = \frac{r_{ij}}{r_{max}}$	[6]
	Cost criteria	$n_{ij} = 1 - \frac{r_{ij}}{r_{max}}$	
Linear (Max - Min)	Benefit criteria	$n_{ij} = \frac{r_{ij}}{r_{max}}$	[7]
	Cost criteria	$n_{ij} = 1 - \frac{r_{ij} - r_{min}}{r_{max} - r_{min}}$	
Linear (Sum)	Benefit criteria	$n_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$	[8]
	Cost criteria	$n_{ij} = \frac{\frac{1}{r_{ij}}}{\sum_{i=1}^{m} \frac{1}{r_{ij}}}$	
Vector (Max)	Benefit criteria	$n_{ij} = \frac{1}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$	[8]
	Cost criteria	$n_{ij} = 1 - \frac{1}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$	
Logarithmic	Benefit criteria	$n_{ij} = \frac{\ln(r_{ij})}{\ln(\prod_{i=1}^{m} r_{ij})}$	[8]
	Cost criteria	$n_{ij} = 1 - \frac{\ln(r_{ij})}{\ln(\prod_{i=1}^{m} r_{ij})}$	
Enhanced accuracy	Benefit criteria	$n_{ij} = 1 - \frac{r_{ij}^{max} - r_{ij}}{\sum_{i=1}^{m}(r_{ij}^{max} - r_{ij})}$	[8]
	Cost criteria	$\boldsymbol{n_{ij} = 1 - \frac{r_{ij} - r_{ij}^{min}}{\sum_{i=1}^{m}(r_{ij} - r_{ij}^{min})}}$	

where $n_{ij} = [r_{ij}]mxn$ is the Decision matrix, where r_{ij} is the performance value of i[th] alternative and j[th] attribute, m is the number of available alternatives and n is the number of attributes.

The productivity, salt rejection, and differential pressure trends can all be used to assess the impact of any membrane system alteration. Operators can, for example, test the effect of applying permeate back pressure to balance flows from different stages of multi-stage systems, in addition to changes in membrane flux and recovery [9]. The calculations of (1) Pressure correction factor (PCF), which accounts for pressure, concentration, and conversion effects, (2) Temperature correction factor (TCF), which accounts for temperature effects, and (3) membrane flux retention coefficient (MFRC), which accounts for the effect of temperature and pressure on membrane compaction with time, is required to normalize the performance of SWRO plants [4].

Using the correction factors, the data is standardized from real operating circumstances to standard reference test parameters of 56 kPa pressure, 25 °C feed temperature, and 35 000 mg/l feed TDS concentration. PCF is calculated using Eq. 1:

$$PCF = \frac{P_{fs} - \Delta P_{fbs} - P_{ps} - \pi_{fbs} - \pi_{ps}}{P_{fa} - \Delta P_{fba} - P_{pa} - \pi_{fba} - \pi_{pa}} = \frac{NDP_s}{NDP_a} \; Eq. 1$$

Where:

P_{fs} and P_{fa} - Pressure applied at standard and actual conditions respectively; ΔP_{fbs} and ΔP_{fba} – Device pressure drop at standard and actual conditions respectively; P_{ps} and P_{pa} – Permeate pressure at standard and actual conditions respectively; πfbs and π_{fba} – Feed-brine osmotic pressure at standard and actual conditions respectively; π_{ps} and π_{pa} – Permeate osmotic pressure at standard and actual conditions respectively, π_{ps} and π_{pa} – Permeate osmotic pressure at standard and actual conditions repectively, *NDPs* – Net driving pressure (*Pnet-s*) at standard conditions and *NDPa* – Net Driving pressure (*Pnet-a*) at actual conditions [10].

The temperature correlation factor (TCF) for a given RO plant is calculated by Eq. 2:

$$TCF = e^{\left[\frac{E_m}{R}\left(\frac{1}{273+T} - \frac{1}{298}\right)\right]} \; Eq. 2$$

Where E_m – membrane activation energy, R – gas constant and T – temperature [11].

The specific energy consumption (SEC) is one of the most important parameters to be optimised in a RO desalination plant. Estimation of the normalised specific energy consumption (NSEC) uses a concept that involves osmotic pressure according to the modified Eq. 3:

$$NSEC = \frac{Total\ power\ consumption}{Volume\ of\ water\ produced} * \frac{TCF}{\pi} \; Eq. 3$$

Where π – osmotic pressure. Plants with a capacity of less than 50 000 m^3/d were projected to have greater NSEC values than those with a capacity of more than 50 000 m^3/d [12].

Membrane flux retention coefficient (MFRC), is given by Eq. 4:

$$MFRC = \frac{Q_t}{Q_i} \approx \frac{F_t}{F_i} \; Eq. 4$$

Where Q_t/Q_i – permeate flow rate slope and F_t/F_i – flux decline slope. When just flux decline effects are examined, the MFRC value expresses the amount of flow (flux) retained by a permeator relative to its original flow rate [4].

Membrane manufacturers such as DOW Filmtec advise on cleaning if the following operational parameters are reached:

- The normalized permeate flow drops 10 %
- The normalized salt passage increases 5 % to 10 %
- The normalized pressure drop (feed pressure minus concentrate pressure) increases 10 % to 15 %.

If cleaning is not done at the above stage, then membranes risk not being restored to normal working conditions [13]. Chu et al. [12] validated the SEC normalization under different conditions through comparison with different plants.

3. METHOD

The performance of one of the operational trains of the Victoria and Alfred (V & A) desalination plant located in Cape Town, South Africa, was analysed and evaluated in the month of November 2018. The information about the membranes used in the SW100-10 train is summarised in table 2 and table 3.

Table 2: DOW SW30XLE-440i Membrane Specifications.

Membrane Element	DOW SW30XLE-440i
No. of vessels	6
No. of membranes in each vessel	1
Total no. of membranes	6
Max. operating temperature/ (°C)	45
Max. operating pressure/ (bars)	83
Salt rejection/ (%)	99.8
pH range	2 to 11
Membrane area/ (m^3)	41
Membrane polymer	Polyamide thin-film composite

Table 3: DOW SW30-ULE-440i Membrane Specifications

Membrane Element	DOW SW30-ULE-440i
No. of vessels	6
No. of membranes in each vessel	6
Total no. of membranes	36
Max. operating temperature/ (°C)	45
Max. operating pressure/ (bars)	83
Salt rejection/ (%)	99.7
pH range	2 - 11
Membrane area/ (m^3)	41

The average monthly parameters were as follows:

Recovery - 31 %

$Q_{permeate}$ - 1367 m^3/d

Q_{feed} - 4446 m^3/d

Q_{brine} - 3079 m^3/d

Average feed TDS - 32800 mg/l

Average permeate TDS - 490 mg/l

Average feed temperature - 16 °C

Average feed pH - 7.2

Average feed pressure - 55 bar

The schematic diagram of the plant is shown in Figure 1.

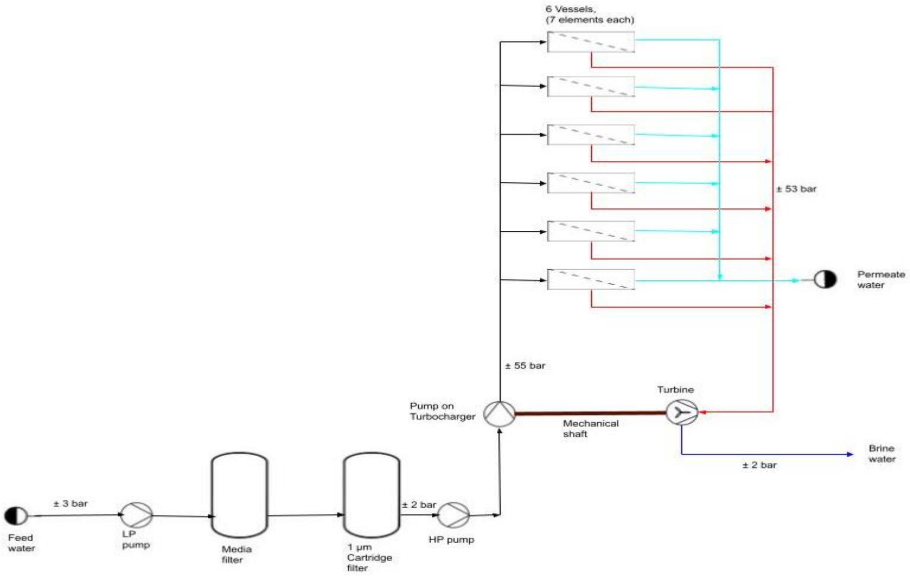

Figure 1: SW 100-10 Train Schematic Diagram [14].

Normalization was performed using Dupont powered FilmTec FTNorm reverse osmosis and nanofiltration operating data normalization Excel sheet. figure. 2 to figure. 5 show the normalized data of the plant. Figure 2 represents the normalized permeate flow for the selected days in the month of November.

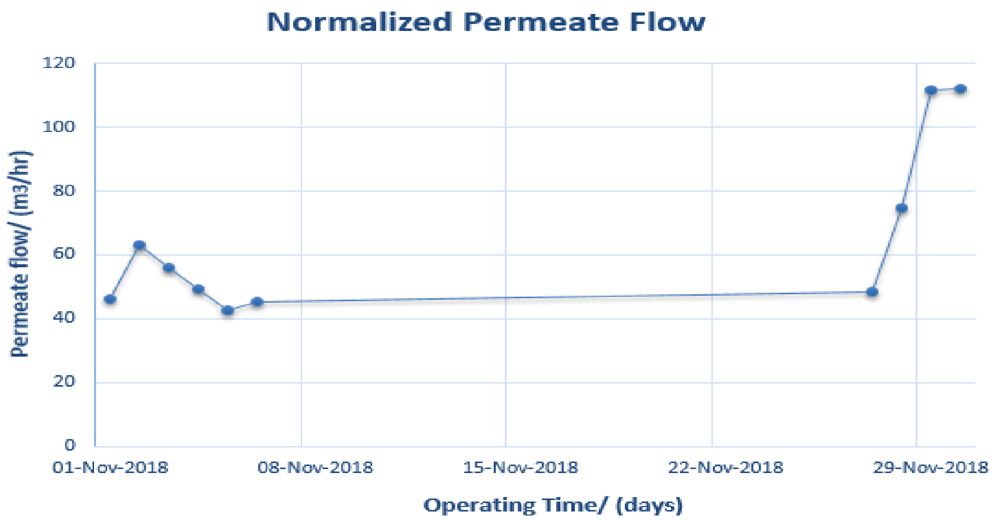

Figure 2: Normalized Permeate Flow Chart for the Month of November.

Figure 3 shows the graphs of normalized salt passage and salt rejection for the plant.

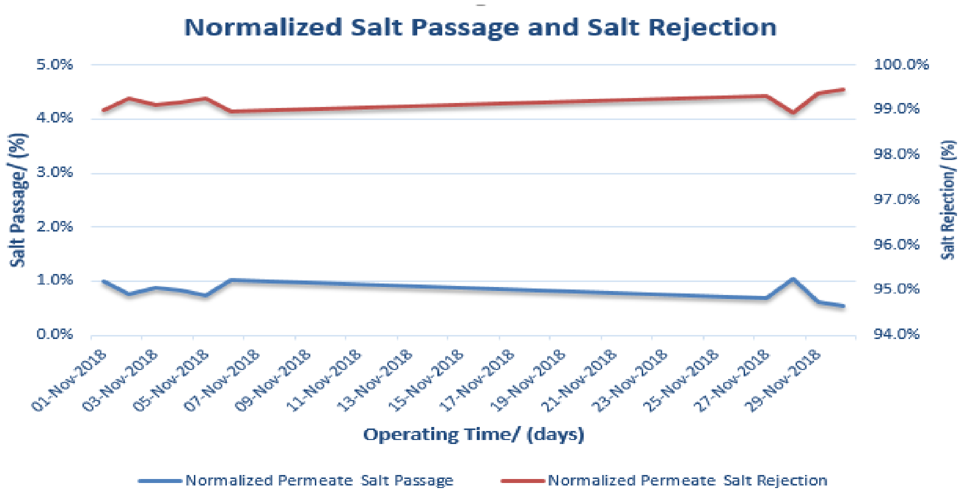

Figure 3: Normalized Salt Passage and Salt Rejection Chart.

Figure. 4 is a representation of differential pressure for the V & A desalination plant. A membrane system's pressure drop from the feed to the concentrate end provides information on the feed channel spacer's fouling [15].

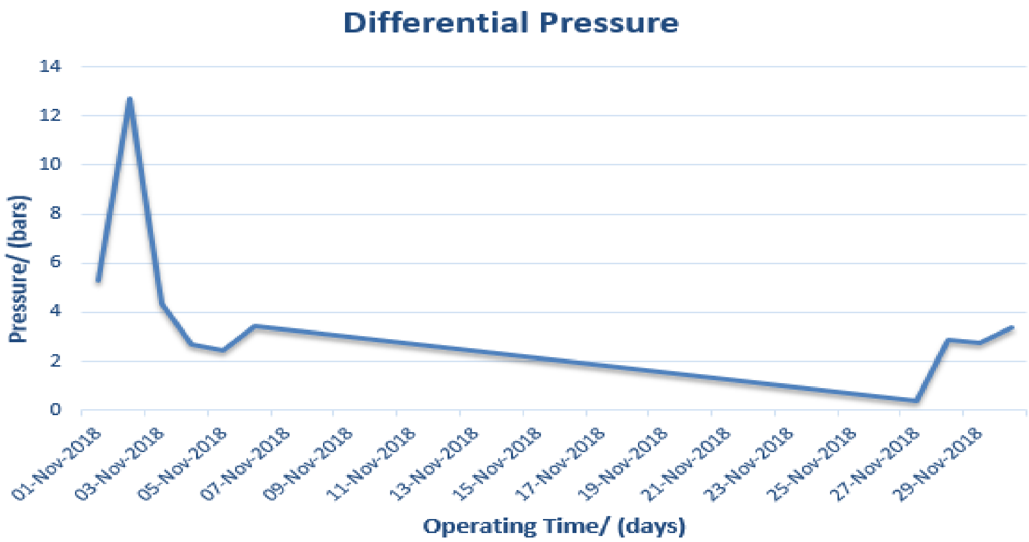

Figure 4. Normalized Differential Pressure Chart.

4. SIMULATION

The simulation was conducted on the extracted data using DuPont powered water application value engine (WAVE) modeling software for water treatment plant design. WAVE integrates three technologies: ultrafiltration (UF), reverse osmosis (RO), and ion exchange (IX), into one tool [16]. Most of the variables for the SW100-10 plant were extracted from experimental values whereas some values were assumed. Table 4 and Table 5 summarize the assumed data and experimental data extracted from the plant and simulated results respectively. DOW SW30 ULE 440i membranes are now obsolete therefore all the membranes were assumed to be DOW SW30 XLE 440i.

Table 2: Assumed and Experimentally Extracted Values for Different Parameters [17].

Parameter	Assumed Value	Experimental Value
$Q_{permeate}$ [m^3/d (m^3/h)]	460 (20)	
Q_{feed} [m^3/d (m^3/h)]	1480 (62)	
Average temperature, (T/ °C)	14.5	
Average pH	7.2	
Average pressure (P/ bars)	55	
Recovery (%)		31
Feed TDS (mg/l)		33728
DOW SW30 XLE 440i	7 membranes	
DOW SW30 ULE 440i		(Obsolete)
No. of vessels		6

Table 3: Simulated Results of the V & A Desalination Plant [17].

Parameter	V & A Desalination Plant	Simulated Value	Error (%)
Permeate flow (m^3/h)	19	20	5
Feed TDS (mg/l)	33 728.88	33 619	0.3
Permeate TDS (mg/l)	399.79	104	73
Feed pressure (bars)	55	46.7	15
Energy consumption (kWh/m^3)	6.58	5.68	13.7
Peak power (kW)	125	113.5	9.2
Recovery (%)	31	31	0
Rejection (%)	98.81	99.69	0.9

The following graphs were obtained from the WAVE simulation project. The simulated permeate flow is represented in Figure. 4 as illustrated. Figure 5 shows the simulated salt passage and salt rejection chart and Figure. 6 represents the simulated differential pressure of the plant.

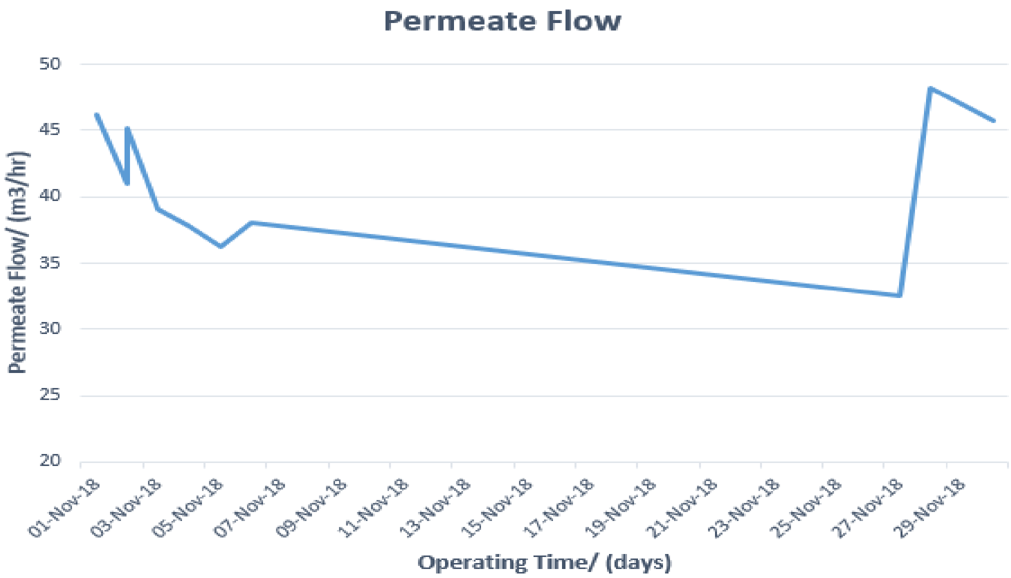

Figure 5: Simulated Permeate Flow for the Plant.

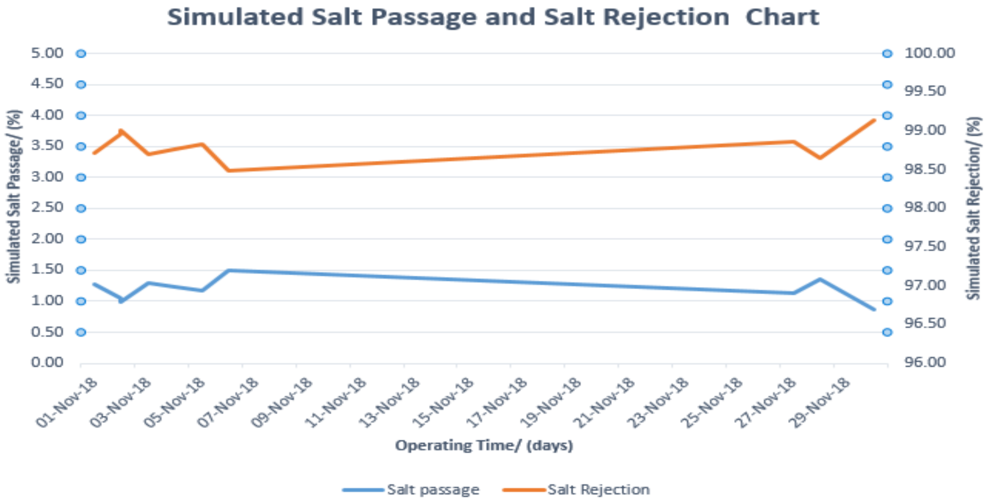

Figure 6: Simulated Salt Passage and Salt Rejection Chart for the Plant.

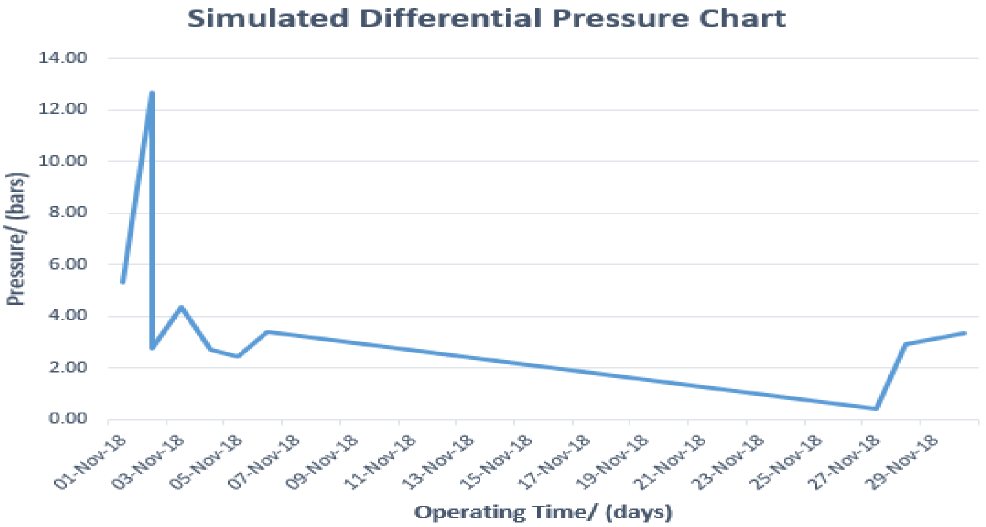

Figure 7: Simulated Differential Pressure Chart.

5. DISCUSSIONS

Normalized differential pressure and simulated differential pressure (Figure. 4 and Figure. 7 respectively) showed no significant differences. This was certified by Kim et al. [2] who stated that because osmotic pressure and TCF are site-specific, it is critical to choose equations that match the feed water and RO membrane parameters in the field for better normalization results. The NPF data group has a smaller variance (or standard deviation) during an operation period without fouling because of its more normalized performance. Selecting proper osmotic pressure and TCF equations which reflect characteristics of water makes fouling detection a bit easier [2]. A sharp increase in differential pressure is seen in the initial operation of the plant. This rapid increase will eventually lead to plant shut down for cleaning purposes, according to Yang et al. [18].

Normalized salt rejection showed a consistent rejection rate of greater than 99 %, whereas the simulated results showed that at one point the salt rejection dropped slightly to around 98 % (Figure. 3). Research conducted by Yang et al. [18] on an industrial steel mill wastewater reuse system showed that the salt rejection in the plant was initially around 98.5

percent, but the normalized rejection increased to 99 percent and eventually steadied. Freire-Gormaly and Bilton [18] agree with the reduction in salt rejection observed [19]. The normalized salt passage calculated was slightly below 1 % whilst the simulated salt passage recorded was slightly above 1 %. The normalized salt rejection and salt passage trend usually remains the same for long periods of plant operation [15]. According to Boulahfa et al. this may be due to the absence of physical or chemical deterioration of the membranes [20].

The normalized permeate flow (NPF) is scattered at the beginning because the plant was operated at a lower than design flow rates (Figure. 2). This is according to the research by Sehn [15]. The NPF is slightly lower at the beginning of the operation. This might be due to scaling or fouling of membranes due to the presence of salts in the feed water [20].

6. CONCLUSIONS

Normalizing and standardizing data using available computer tools enable operators to carry out tasks such as system optimization. Most operators ought to employ these tools to help them maintain their membrane systems. It is feasible to see the effects of changing feed water by trending the normalized system values to determine if the existing source water mix needs to be altered by assessing these standardized system values. It is also feasible to figure out whether or not additional pretreatment is required. The results show that normalizing the plant results in an improved and optimized plant and early detection and identification of potential problems.

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